Potential of Active Demand Reduction with Residential Wet Appliances: A Case Study for Belgium

Wouter Labeeuw, *Member, IEEE*, Jeroen Stragier, Geert Deconinck, *Senior Member, IEEE*

***Abstract*—Two problems are tackled in this paper: determining the active demand reduction potential of wet appliances and making time series estimates from project data. The former is an application of the latter. Household groups representative to the average population are defined by applying Expectation Maximization clustering to a representative measurement set ($n = 1363$). Attitudes towards active demand are found by conducting a survey ($n = 418$). Project data ($n = 58$) containing wet appliance measurements are scaled up by adapting the clustering algorithm, spreading the electricity demand of the wet appliances over the clusters. The potential for active demand reduction with wet appliances is 4% of the total residential power demand, assuming that 29% of the households take part. The potential is in the order of magnitude of the power reserves, but does not fulfill availability and response time requirements.**

***Index Terms*—Clustering, demand response, residential, wet appliances**

I. Introduction

A. Demand response

Demand response is described by the U.S. Department of Energy as 'Changes in electric use by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.' [1]. However, lower electricity use is not essential for demand response. A more recent definition, from the European University Institute, focuses on the active part and goes as follows [2]: 'Changes in electric usage implemented directly or indirectly by end-use customers/prosumers from their current/normal consumption/injection patterns in response to certain signals.' Active demand response, or short active demand, refers to directly controlled demand response.

The literature defines many driving forces behind demand response: more efficient markets and the accompanied price reductions [3], the avoidance of black outs due to a small amount of demand response [4], lower capacity of installed generation, improved operation efficiency of the transmission grid, a lower required investment in the transmission and the distribution net and balancing of renewables [5].

W. Labeeuw and G. Deconinck are with the Department of Electrical Engineering (ESAT), ELECTA, KU Leuven, Belgium and EnergyVille (email: wouter.labeeuw@esat.kuleuven.be and geert.deconinck@esat.kuleuven.be).

J. Stragier is with the Department of Communication Sciences, iMinds-MICT, UGent, Belgium (email: jeroen.stragier@ugent.be).

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However, a lot of uncertainties still need to be tackled. Who will pay for the installation costs of the demand response equipment is the most common question [3], [4], [6]. The limited knowledge about the potential savings and expected high costs is a concern for policy makers [7]. Furthermore, customers should be able to comprehend the representation of the price and the incentives and the incentive should be high enough for them to care [8].

Insights about the willingness of customers to participate in and the effects of demand side management are provided by field tests. Various studies measured the response to time of use tariffs; the response varied from study to study [9]. Automated residential demand response has been tested in Richland, Washington, USA, using water heaters, thermostatically controlled heating, and ventilation and air conditioning systems in 112 homes, approaching 1.5 kW per home. The project demonstrated effectively shifting energy towards very early morning hours when electricity is least expensive [10]. A demand response program in Norway with 40 participating households found a 1 kWh/h demand response for customers with electrical water heaters [4], but reported that the customers with interest in their electricity consumption were over-represented. A Swedish program with 50 households showed a shift of the peaks to off-peak periods and a growing awareness which resulted in higher shifts at the end of the study [11]. An Italian study found that time of use tariffs bring about higher average electricity demand and lower customer payments. Loads were shifted in the morning, but the evening peaks were not resolved [12].

The field test used in this work to estimate the potential of active demand reduction of wet appliances consist of electricity demand measurements and an attitude study. Only the reduction part (not the rebound) is considered because no information about delay durations is available. The focus is on residential wet appliances: washing machines, tumble dryers and dishwashers. Little is known about the potential of active demand with those.

B. Problem statement

Making statements from field test measurement data is often difficult: customers with a high interest in their electricity consumption are more eager to participate in a smart grid or a demand response program [4], [13]. Simple random sampling will select customers in proportion to the sampling frame, i.e., the people willing to participate, which will result in a selection of customers with a positive attitude towards active demand. Stratified sampling copes with the given problem by defining mutual exclusive and exhaustive groups. However, strata are costly to calculate when the distributions of combinations over demographic properties are not available, e.g., what is the probability of a household living in a semi-detached house, with a moderate electricity demand, four inhabitants and the head being between 35 to 44 years old. Quota optimization could be a solution [13], but some projects prefer to roll out as much appliances as possible per household to reduce costs, hence not meeting the required quota, and require a new approach to extrapolate the results. A technique to make estimations from a limited non-representative set of data is presented in this paper.

Also, few publications describe how appliances are used and what their corresponding electricity demand is, especially wet appliances. Recent work describes the individual load profiles of a range of appliances in more detail [14]. However, the most relevant work made load curves based on surveys and questionnaires [15] and monitoring [16], [17]. The electricity demand of those wet appliances gives insights about the possibilities for demand reduction with those appliances. The technique to make estimations from a limited non-representative set of data is applied to measurements of wet appliances to estimate the appliance usage and, in combination with the attitude towards active demand response, the potential thereof.

C. Approach

The approach taken to estimate the potential for active demand by wet appliances is based on clustering. The first requirement is having a representative set of measurement data, for a year, with a resolution of fifteen minutes. The data is clustered based on the timing and the magnitude of electricity demand. The found clusters are the models to represent the whole population. In order to allow for data upscaling, when insufficient data is available, the cluster models need to be adjusted.

The representative set of measurements consisting of load profiles measured at the point of common coupling of a set of households representative for Flanders (the northern half of Belgium) has been provided by distribution system operators (DSOs). The households are grouped using a clustering algorithm.

To assess the potential of active demand with wet appliances, knowledge about attitude towards active demand is required. A large subset of the representative set (from the DSOs) has been interviewed. The responses are clustered to find common attitudes, with each household having one dominant attitude. Due to non-response, the households needed to be weighted according to age and number of inhabitants. The households are each appointed to a representative group, resulting in the probabilities of the attitudes within those groups.

The appliance usage is the other important factor. A smaller number of households has been monitored in the ‘Local Intelligent Networks and Energy Active Regions (Linear)’-project [18]. Appointing each household to one of the representative groups would limit the amount of data per group. Therefore, each household is appointed to multiple representative groups by using the adapted cluster models, resulting in an up-scale of the data. The households are, in this way, spread over the representative groups.

By spreading the households over the representative groups, appliance measurements are spread as well. Only households owning the appliance are considered, hence the spread appliance measurements need to be scaled according to the appliance ownership rates to find how they are used (in terms of electricity demand) within a representative group. By scaling those demands with attitudes towards active demand, estimates about the potential for active demand with wet appliances are made.

D. Paper organization

The remainder of the paper is arranged as follows. The data for the analyses is described in Section II. The reasoning behind the choice of the clustering algorithm, a description of the selected algorithm and the adaption of the algorithm for data upscaling purposes are explained in Section III. The segmentation of the population into various attitudes towards active demand response is elaborated upon in Section IV. Section V describes how the data of a project is scaled up using the adapted clustering algorithm of Section III; measurements from wet appliances are scaled up to find how those appliances are used within a given cluster. Finally, in Section VI, the potential for active demand reduction with wet appliances, expressed in MW, is estimated based on the appliances' demand in a cluster and the attitude towards active demand.

II. Data description

The Flemish distribution grid operators jointly monitor the electricity demand at the point of common coupling of a representative set of households for the regulator. 1693 households were monitored on a 15 min interval over the period 2006-2009. 1363 of the 1693 households were monitored in 2008.

An in-home survey is conducted in 500 of those monitored households to get an idea of the demographic properties of the households. 418 of the 500 surveyed households have metering information of 2008. The survey included questions related to demography, ecology, mobility, buildings, insulation, heating, energy demand, appliances, ICT and direct load control.

Age, number of inhabitants and having a business or not are the most influential parameters regarding total annual electricity consumption and the variation on the electricity demand [13]. In the survey, elderly persons and households of two persons over-responded. To compensate, each household is weighted according to both relative difference in age (Table I) and number of inhabitants (Table II). The weights make sure that the distribution of the survey respondents (sample and size) resembles the Belgian population better. A more suitable weighting technique would have been weighing relative to the joint probability of the age and the number of inhabitants. Unfortunately, the Belgian Directorate General for Statistics and Economic Information does not provide information of these joint probabilities.

TABLE I
AGE DISTRIBUTION OF THE TOTAL POPULATION, THE SAMPLE AND THE WEIGHTED SAMPLE

Age	Pop. [%]	Sample [%]	Weighted [%]	Size
18 - 34	23.4	4.8	14.0	20
35 - 44	19.1	10.3	15.3	43
45 - 55	19.0	23.0	21.1	96
56 - 64	15.6	28.2	20.5	118
$\geq$ 65	22.9	33.7	29.1	141

TABLE II
DISTRIBUTION OF THE NUMBER OF INHABITANTS OF THE TOTAL POPULATION, THE SAMPLE AND THE WEIGHTED SAMPLE

Inhabitants	Pop. [%]	Sample [%]	Weighted [%]	Size
1	29.8	17.5	22.3	73
2	34.2	47.9	36.6	200
3	15.8	17.9	19.4	75
4	13.7	10.8	14.2	45
$\geq$ 5	6.6	6.0	7.6	25

The electricity demand at the point of common coupling and at appliance level of 58 households is measured for a whole year in the 'Linear'-project. Not all measurement data could be used for analysis purposes. The measurements of the electricity demand at the point of common coupling had issues related to the in-home data communication infrastructure in some cases. Reliable 15 min measurement data were obtained from 30 households with a washing machine, 27 households with a tumble dryer and 21 households with a dishwasher.

III. HOUSEHOLD GROUPING

A. Clustering algorithms

Household grouping based on consumption is mainly done by clustering load profiles. The most common algorithms to cluster electrical loads, as explained in [19], are k-means (KM) [20]–[23], fuzzy k-means (FKM) [20]–[23], hierarchical [20]–[22], modified-follow-the-leader [20], [21] and Expectation Maximization (EM) [24] clustering, and self organizing maps (SOM) [20], [21], [23], [25]–[27].

KM and FKM keep cluster populations relatively uniform, but detect outliers to a much lesser extent than hierarchical and modified-follow-the-leader clustering [21]. KM performs slightly better than FKM in the stability index [23] and FKM on its turn performs better than SOM. Coke et al. [24] pointed out that mixture models are better in smoothing random effects and applied a modified Expectation Maximization clustering.

The goal of clustering in this application is getting an overview of large uniform groups within the population. Therefore, KM and FKM are preferred over hierarchical and modified-follow-the-leader clustering. A non-fuzzy technique (KM) performs better than a fuzzy one (FKM). However, relaxation is needed for data upscaling. Both FKM and EM clustering allow for this. Because of the smoothing effect and the possibility to easily relax cluster membership, EM clustering is selected for following analyses.

EM clustering uses Gaussian distributions to model data. Distributions of electrical power are usually a skewed. However, by combining Gaussian distributions, skewed distributions can be approximated.

B. Expectation Maximization

The used clustering algorithm is Expectation Maximization [28]. Bayes' theorem is the basis for the algorithm. The probability of an instance i belonging to a cluster cl is described by,

$$P(\mathbf{S}_{cl}|\mathbf{x}_i) = \frac{P(\mathbf{S}_{cl}) \cdot P(\mathbf{x}_i|\mathbf{S}_{cl})}{P(\mathbf{x}_i)} = P(\mathbf{x}_i \in \mathbf{S}_{cl}) \quad (1)$$

where $P(\mathbf{S}_{cl})$ is the probability of the cluster (the prior), $P(x_i|\mathbf{S}_{cl})$ is the likelihood of x_i given $\mathbf{S}_{cl}$ and $P(\mathbf{x}_i)$ as a normalizing constant, defined by,

$$P(\mathbf{x}_i) = \sum_{j=1}^{n_c} P(\mathbf{S}_j) \cdot P(\mathbf{x}_i|\mathbf{S}_j) \quad (2)$$

The model to describe the data distribution is a Gaussian distribution. A Gaussian distribution is calculated for each dimension d of the data set. The likelihood of an instance i being taken from the Gaussian distribution of a cluster cl in dimension d is defined by the probability density function value pdf which relies on the mean μ and the standard deviation σ in the dimension d of cluster cl,

$$pdf_{i,cl,d} = \frac{1}{\sqrt{2\pi\sigma_{cl,d}{}^2}} e^{-\frac{(x_{i,d}-\mu_{cl,d})^2}{2\sigma_{cl,d}{}^2}} \quad (3)$$

Assuming Naive Bayes [28], i.e., the individual probabilities are independent, the overall likelihood of instance i belonging to cluster cl is obtained by multiplying the different probability density values,

$$P(\mathbf{x}_i|\mathbf{S}_{cl}) = \prod_{d=1}^{n_d} pdf_{i,cl,d} = \exp\left(\sum_{d=1}^{n_d} \log pdf_{i,cl,d}\right) \quad (4)$$

The numerator of Bayes' theorem (the density) can be rewritten as,

$$P(\mathbf{S}_{cl}) \cdot P(\mathbf{x}_i|\mathbf{S}_{cl}) = \prod_{d=1}^{n_d} pdf_{i,cl,d} \cdot P(\mathbf{S}_{cl}) \quad (5)$$

The logarithm of the density is,

$$\log dens_{i,cl} = \sum_{d=1}^{n_d} \log pdf_{i,cl,d} + \log P(\mathbf{S}_{cl}) \quad (6)$$

The EM algorithm can be executed as a classifier (hard) or fuzzy (soft). In the hard case, the instance is assigned to the cluster with the highest likelihood, i.e., the probability of the most likely cluster will be one. The (soft) probability of belonging to a cluster is calculated by combining Equations 5, 2 and 1. To make the calculation numerical more stable, the probabilities are normalized. Equation 5 is replaced by subtracting the maximum log density from all densities,

$$P(\mathbf{S}_{cl}) \cdot P(\mathbf{x}_i|\mathbf{S}_{cl}) = \exp\left(\log dens_{i,cl} - \arg\max_{cl} \log dens_{i,cl}\right) \quad (7)$$

TABLE III
CLUSTERS OF HOUSEHOLDS, BASED ON CONSUMPTION, CONSUMPTION TIMING AND HAVING A BUSINESS OR NOT

Type	Sub-type	Annual consump. [kWh]	Households [%]
Day	small	800	14.1
	rel. small	2 500	25.9
	average	4 250	27.8
	rel. large	6 650	15.4
	large	11 600	7.7
Night	average	6 200	3.2
	large	8 750	2.9
Business	average	28 350	2.3
	rel. large	70 000	0.5
	large	189 600	0.1

The Gaussian models are updated during the Maximization step. Each cluster cl has a Gaussian model in every dimension d, which consists out of a mean μ,

$$\mu_{cl,d} = \frac{\sum_{i=1}^{n_i} P(\mathbf{x}_i \in \mathbf{S}_{cl}) \cdot x_{i,d}}{\sum_{i=1}^{n_i} P(\mathbf{x}_i \in \mathbf{S}_{cl})} \tag{8}$$

and a standard deviation σ,

$$\sigma^2_{cl,d} = \frac{\sum_{i=1}^{n_i} P(\mathbf{x}_i \in \mathbf{S}_{cl}) \cdot (x_{i,d} - \mu_{cl,d})^2}{\sum_{i=1}^{n_i} P(\mathbf{x}_i \in \mathbf{S}_{cl})} \tag{9}$$

The algorithm stops iterating between the Expectation and the Maximization step when the overall likelihood stops changing significantly between iterations. Significance is expressed as a threshold TH. The threshold is defined experimentally at 10^{-10} for 10 successive iterations [28]. The stopping criterion is,

$$\left(\sum_{k=1}^{n_k} \sum_{cl=1}^{n_{cl}} \log dens_{k,cl}^{(t+1)} - \sum_{k=1}^{n_k} \sum_{cl=1}^{n_{cl}} \log dens_{k,cl}^{(t)} \right) \leq TH \tag{10}$$

The load profiles, i.e., the sequence of power measurements, of the households are transformed in load curves, representing the average electricity demand during the day for the average week per quarter of the year for each household, to lower the dimensionality of the data. The dimensionality reduces thus from 35040 measurement points to 2688 points. Load curves capture the average magnitude and the timing of consumption. The number of clusters has been limited to ten, double the number of day consumer types defined by the regulator [29] and low enough to limit the number of outlier groups. Clustering with the above described Expectation Maximization algorithm resulted in ten household groups, representative to Belgium (Flanders). The groups (Table III) are named after the timing and the magnitude of the demand and having a business or not. The relatively large and the large business-consumer groups are considered to be outliers because of their low probability.

C. Cluster membership relaxation

The large number of dimensions resulted in quasi crisp cluster membership: instances make only part of one cluster. By adjusting the cluster membership function, the cluster membership is relaxed, i.e., instances are part of multiple clusters. The relaxation is done by reducing the dimensionality of the likelihoods: the multiplication of the probability density values and the prior (Equation 5) is replaced by the geometric average of the probability density values and the prior.

The reduction of the dimensionality of both the likelihoods and the priors is done by taking the $(n_d + 1)$'th root of the multiplication of both. A numerical more stable method which accomplishes the same is,

$$\log dens_{i,cl} = \frac{\log P(\mathbf{S}_{cl}) + \sum_{d=1}^{n_d} \log pdf_{i,cl,d}}{n_d + 1} \tag{11}$$

The probability of a cluster $P(\mathbf{S}_{cl})$ is negligible in Equation 11 because of the high value for n_d (2688). The equation can thus be interpreted as the average of the likelihoods,

$$P(\mathbf{x}_i|\mathbf{S}_{cl}) \approx \exp\left(\log dens_{i,cl} \approx \frac{\sum_{d=1}^{n_d} \log pdf_{i,cl,d}}{n_d} \right) \tag{12}$$

The probability of an instance belonging to a cluster is hence approximately the normalized likelihood that the instance is drawn from the considered cluster,

$$P(\mathbf{x}_i \in \mathbf{S}_{cl}) \approx \frac{P(\mathbf{x}_i|\mathbf{S}_{cl})}{\sum_{j=1}^{n_{cl}} P(\mathbf{x}_i|\mathbf{S}_j)} \tag{13}$$

The denominator needs to be constant to have normalization, which means that in Equation 13, it is assumed that the models are correct and the starting point for further analyses. The indirect consequence of the assumption is that the probability of each cluster is equal. The result of the relaxation is that data from the clusters with high probability will enter clusters with a lower probability.

The effect of the relaxation is visualized in a correlation matrix representing the correlations between the cluster memberships. Without relaxation, the correlation matrix would only show the diagonal, i.e., only correlation with itself. When a household is appointed to one cluster, membership in the other clusters is always zero, hence correlation is undefined. With relaxation, cluster membership is correlated with neighboring clusters, e.g., the average day consumer (d-a) is related to relatively small day (d-rs) and relatively large day (d-rl) consumers, while there is inverse correlation with small day (d-s), large day (d-l) and business (b-a, b-rl and b-l) consumers. The negative correlation means that if a household is part of the average day consumer cluster, the household is unlikely to be part of the small day consumer cluster.

The effect of the cluster memberships' relaxation is higher electrical powers for the clusters with low and lower electrical powers for the clusters with high electrical power, compared to the original clusters (Figure 2). Both high and low powers regress to the mean.

	d-s	d-rs	d-a	d-rl	d-l	n-a	n-l	b-a	b-rl	b-l
d-s	1.00	0.44	-0.41	-0.77	-0.55	0.22	-0.02	-0.32	-0.10	0.04
d-rs	0.44	1.00	0.42	-0.58	-0.82	-0.20	0.04	-0.68	-0.38	-0.07
d-a	-0.41	0.42	1.00	0.40	-0.36	-0.49	0.00	-0.60	-0.49	-0.15
d-rl	-0.77	-0.58	0.40	1.00	0.61	-0.39	-0.16	0.12	-0.15	-0.10
d-l	-0.55	-0.82	-0.36	0.61	1.00	-0.14	-0.31	0.73	0.30	0.01
n-a	0.22	-0.20	-0.49	-0.39	-0.14	1.00	0.27	0.07	0.14	0.12
n-l	-0.02	0.04	0.00	-0.16	-0.31	0.27	1.00	-0.21	-0.10	0.01
b-a	-0.32	-0.68	-0.60	0.12	0.73	0.07	-0.21	1.00	0.74	0.09
b-rl	-0.10	-0.38	-0.49	-0.15	0.30	0.14	-0.10	0.74	1.00	0.14
b-l	0.04	-0.07	-0.15	-0.10	0.01	0.12	0.01	0.09	0.14	1.00

Fig. 1. Correlation matrix in the relaxed case

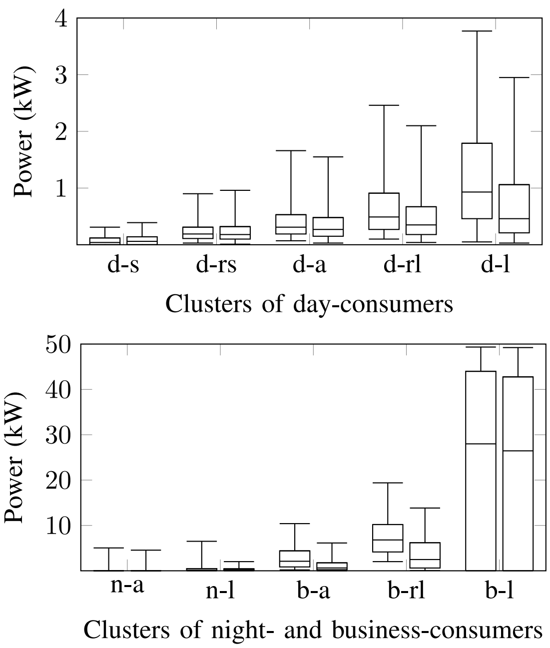

Fig. 2. Distribution of electrical power for original (left) and relaxed (right) cluster data.

IV. Social segmentation

To compute the attitude towards active demand response, a quantitative survey has been held in Flanders in 2010. A total sample of 500 respondents, taken from the 1326 metered households, has been surveyed by means of computer assisted personal interviewing (CAPI) at their home. The survey actively addressed the issue of the consumers' attitude towards active demand, as delivered through smart household appliances. A list of 22 items, operationalizing 9 dimensions of the attitude towards smart appliances has been presented to the respondents. The attitude dimensions measured are: perceived usefulness, perceived ease of use, overall attitude toward using smart appliances and behavioral intention to use.

- 'Perceived ease of use' refers to the degree in which a potential user expects to be able to use new technologies without problems.
- 'Perceived usefulness' refers to the degree in which the potential user expects that the features of the new technology will be useful and provide significant advantages over their current way of working.
- 'Attitude towards using' measures the overall attitude of the respondents towards the new technology.
- 'Intention to use' measures the degree to which the respondent expects to adopt the new technology.

These four dimensions are often used in technology adoption models such as [30] and are widely applicable to various innovations. To make the attitude measurement specific to active demand response appliances, 5 exploratory dimensions are added to the framework: safety, control, comfort, environmental friendliness and cost.

- 'Safety' refers to the degree to which a respondent considers smart appliances to be safe to work with.
- 'Control' stands for the amount of control that a respondents expects to keep over smart appliances.
- 'Comfort' aims to measure the degree to which respondents expect to keep a same level of comfort in his daily life while using smart appliances.
- 'Environmental friendliness' measures how environmentally friendly the respondents expect smart appliances to be.
- 'Cost' measures the degree to which the respondent expects that smart appliances will be more expensive than current appliances.

All of these dimensions are measured by Likert scale items. The 5-point response scale ranged from 'totally disagree' to 'totally agree'. The respondents are clustered on the five dimensions using k-means, an euclidean distance based clustering algorithm. k-means requires data normalization, therefore, min-max normalization is applied to each dimension,

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{14}$$

The algorithm requires initial cluster centers to start with. These are chosen using the maximin algorithm: select the first record as the first center, compute the euclidean distance between the center and each record, select the record with the largest euclidean distance and make it a new center, repeat distance computation and making it a new cluster center until k clusters [31].

The selected initial instances cl are called seeds or cluster centers. An empty set S is associated with each seed. For each new instance i in the data set, the Euclidean distance d between the point $\mathbf{x}_i$ and each seed μ_{cl} is calculated,

$$d_{i,cl}^{(t)} = \left\| \mathbf{x_i} - \mu_{\mathbf{cl}}^{(\mathbf{t})} \right\| \tag{15}$$

Each instance $\mathbf{x}_i$ is added to the next $(t+1)$ set S of the closest seed cl,

$$S_{cl}^{(t+1)} = \left\{ \mathbf{x_i} : d_{i,cl}^{(t)} \leq d_{i,j}^{(t)}, \forall 1 \leq j \leq k \right\} \tag{16}$$

The seeds are updated for the next step and receive the value of the mean of the set:

$$\mu_{\mathbf{cl}}^{(\mathbf{t+1})} = \frac{\sum\limits_{x_k \in S_{cl}^{(t+1)}} \mathbf{x_k}}{\left| S_{cl}^{(t+1)} \right|} \tag{17}$$

The process of calculating distances, adding to seed sets and updating the seeds of the set is repeated until all instances remain within their set.

TABLE IV
SOCIAL SEGMENTATION OF THE GROUPS

Type	Sub-type	Attitude [%] advocate	supporter	skeptic	refuser
Day	small	27.8	16.7	26.6	29.0
	rel. small	28.2	21.6	36.2	14.0
	average	33.9	25.5	21.8	18.9
	rel. large	50.8	35.4	9.7	4.1
	large	18.5	48.0	21.5	12.0
Night	average	48.3	43.2	8.6	0.0
	large	57.9	29.6	12.5	0.0
Business	average	57.9	13.5	17.9	10.7
	rel. large	0.0	36.6	63.4	0.0

TABLE V
APPLIANCE OWNERSHIP RATES OF THE GROUPS

Type	Sub-type	Ownership rate [%] wash. mach.	dryer	dishwasher
Day	small	85.4	46.7	26.3
	relatively small	98.1	69.8	57.4
	average	98.0	83.9	76.7
	relatively large	97.3	86.9	79.5
	large	71.9	60.3	54.1
Night	average	100.	48.3	7.8
	large	100.	87.5	62.8
Business	average	8.83	8.83	34.2
	relatively large	54.9	19.3	100.

The four resulting clusters are considered the social segments and each of the respondents is assigned to one of those: advocates, supporters, skeptics and refusers. A more detailed explanation about the social analysis can be found in [32]. The segments are further used as the attitude score of the respondent in further analysis.

The attitude of the household groups is determined using the individual attitudes. The non-relaxed cluster membership places a household in a group. The relaxed algorithm is not needed, given that there is sufficient survey data. The distribution of the individual households gives an overview of the attitudes within the group, as shown in Table IV. The large business consumer group is not presented due to lack of data.

Adding the attitude segmentation data based on survey results to the clustering adds a potentially important factor to the analysis. Estimations of DR potential are often based on usage data [33], which may however neglect the importance a consumer's position towards the introduction of new technology. Earlier research [30], [34] has confirmed this attitude as an important precursor of effective technology adoption and use.

V. WET APPLIANCES

A. Ownership rates

The survey is also used to determine the appliance ownership rates of the various groups based on the non-relaxed group membership (sufficient data). The ownership rates are presented in Table V.

B. Groups of households

The metered households in the 'Linear'-project are spread over the groups according to the relaxed cluster membership (data needs to be scaled up). The load profile containing the electricity demand at the point of common coupling of the house is converted into a load curve of the household. The load curve is presented to the cluster models to calculate the probability of belonging to that cluster (Equation 13).

The sum of the calculated probabilities (Table VI, $\sum p$) provides information about how the households of the project are spread over the groups. The relaxed cluster appoints a household to a cluster and neighboring clusters, as shown by the correlation between clusters (Figure 1). Usually, the probability on the most important cluster is higher than 0.3; the neighboring clusters have a weight above (or around) 0.2. A weight higher than 0.2 (Table VI, $\#p{>}0.2$) thus refers to the most important clusters for the considered household. More households with a large probability means more dominant instances in the group. The sum of the dominant instances over all clusters is larger than the number of households, which means upscaled data.

Some groups are badly represented, given the low probability sum (Table VI, $\sum p$) and the low number of probabilities being higher than 0.2. Insufficient data is available for small day-consumers, average night-consumers, and relatively large and large business-consumers. Those groups are discarded in the following analyses.

Load curves of the wet appliances are created per cluster group by taking the weighted sum of the load curves of the individual appliances, using the relaxed cluster membership of the households. The mean, median and the maximum values of the resulting load curves are presented in Table VII.

Figure 3 shows the wet appliances' load curves of the average day-consumer who owns the respective appliance. The presented appliances are washing machines (WM), tumble dryers (TD) and dishwashers (DW). The load curves represent the electricity demand during the averaged day of the year. The curves reveal the tariff schemes in Belgium. The tariffs schemes are day tariff (between 6h and 21h or 7h and 22h, depending on the distribution system operator), night tariff (during the weekend and when not day) and exclusive night tariff (8 to 9 hours during the night, only for heating purposes). The tariffs for the respective schemes in June 2008 were around 20.7 c€/kWh, 16.8 c€/kWh and 10.6 c€/kWh [35]. A flat tariff also exists with a price in between day and night tariff.

Night tariff scheme is clearly visible in the load curves of dishwashers (Figure 3). On weekdays, the average demanded power is much higher after 10 pm than during the rest of the day. The late evening peak is smaller during weekends. Higher demand occurs after meals, especially during weekends.

The relatively high electricity demand of washing machines after 10 pm during weekdays (Figure 3) is also due to night tariff. The shape and size the load curve is comparable to [15], but the curve is shifted in time. Also, the peak is higher in the morning and the slope is downwards compared to flat in [15].

The load curve of the tumble dryers has no peak at the start of night tariff, as shown in Figure 3. The shape of the load

TABLE VI
HOW THE HOUSEHOLDS MEASURED IN THE PROJECT ARE SPREAD OVER THE GROUPS

Type	Sub-type	Washing machine		Tumble dryer		Dishwasher	
		$\sum p$	$\#p > 0.2$	$\sum p$	$\#p > 0.2$	$\sum p$	$\#p > 0.2$
Day	small	0.023	0	0.023	0	0.021	0
	relatively small	2.255	6	1.918	5	1.396	4
	average	8.271	23	6.924	19	5.502	16
	relatively large	9.329	24	8.612	22	6.447	17
	large	5.377	9	5.139	10	3.702	7
Night	average	0.000	0	0.000	0	0.000	0
	large	2.783	2	2.504	2	2.007	2
Business	average	1.791	1	1.715	1	1.711	1
	relatively large	0.169	0	0.163	0	0.212	0
	large	0.003	0	0.002	0	0.002	0
Total		30	65	27	59	21	47

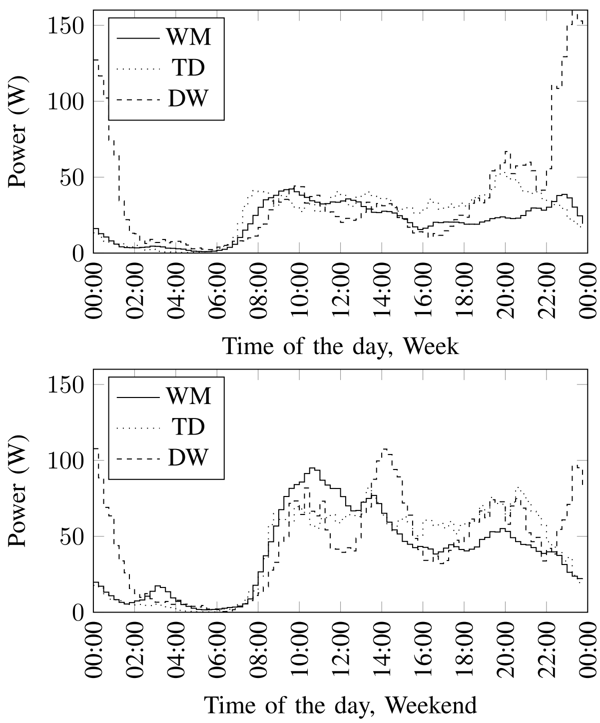

Fig. 3. Wet appliance load curves for the average day-consumer

curve is almost identical to the load curve in [15]. However, the average power in the load curve by [15] is three times as large namely around 103 W. This results in an electricity demand of 900 kWh on yearly basis, while 250 kWh is more likely. An explanation for the difference can be found in the ownership rate, which is 36% in [15] while much higher (Table V) here.

VI. POTENTIAL FOR ACTIVE DEMAND REDUCTION

In this paper, active demand response is considered to be the amount of delayable power. Because no information about the duration of the delay is currently available, only the curtailment part is assessed. The power demanded by wet appliances over the population is determined by scaling the appliances' power demand for people owning the devices with the ownership rates. The delayable power is calculated by scaling the appliances' power demand over the population by

TABLE VIII
POTENTIAL FOR ACTIVE DEMAND REDUCTION OF WET APPLIANCES PER HOUSEHOLD IN BELGIUM

Type	Subtype	Potential [W]		
		mean	med.	max
Day	relatively small	16.0	15.5	63.7
	average	27.3	27.3	99.7
	relatively large	44.1	39.9	173.1
	large	11.3	9.6	51.0
Night	large	42.0	36.2	152.7
Business	average	16.2	8.9	148.5

the probability of the most positive attitude towards active demand in the population.

The load curves of the appliances of each household are spread over the groups (using the relaxed cluster membership, their mean, median and maximum values are represented in Table VII) and scaled by the respective appliance ownership rates given in Table V to find the appliance load curve per group.

The load curves per group are then scaled by the most positive attitude towards active demand (i.e., advocates) as given in Table IV to determine the potential for active demand reduction. Table VIII shows the mean, median and maximum potential per average customer in the groups. The groups with sufficient appliance data represent 82% of all households, as can be derived from Tables III and VI. The remaining 18% are assumed not to participate in active demand.

The potential for active demand reduction in Belgium is obtained by multiplying the potential per household with the number of households in Belgium, 4.6 million. 29% of the households (1.3 million) participate in active demand by these assumptions, which may be an overestimation. The potential per household is 20.8 W (5.2 Wh per 15 minutes) on average. The annual electricity demand of a typical (median) household is 3.6 MWh, which corresponds to an average power of 410 W. The average potential for Belgium is estimated at 96 MW, which corresponds to 24 MWh per 15 minutes. The median is 92 MW and the maximum is estimated to be 353 MW. Figure 4 visualizes the potential for Belgium.

The 96 MW potential is low compared to the installed capacity of 19.6 GW (2011) [36], peak demand of 13.1 GW or average demand of 9.3 GW and also when only the residential sector is taken into account (2.3 GW) [37]. However, compared

TABLE VII
MEAN, MEDIAN AND MAXIMUM LOAD CURVE POWER DEMAND PER APPLIANCE PER HOUSEHOLD OWNING THE APPLIANCE

Type	Sub-type	Washing machine [W]			Tumble dryer [W]			Dishwasher [W]		
		mean	median	max	mean	median	max	mean	median	max
Day	relatively small	21.75	16.17	106.48	25.18	23.86	103.90	30.90	25.34	135.61
	average	25.92	24.30	146.25	29.36	29.18	114.77	39.21	29.12	190.50
	relatively large	28.16	26.50	170.51	34.13	31.61	151.00	37.46	26.97	201.41
	large	28.56	25.79	200.70	33.99	29.57	156.36	37.16	24.42	248.49
Night	large	25.60	22.64	136.70	28.46	25.18	134.12	35.28	21.38	206.36
Business	average	27.68	24.45	214.23	33.09	27.96	169.61	41.52	19.36	410.16

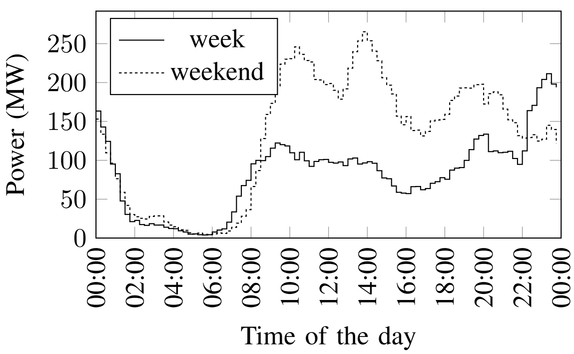

Fig. 4. Estimated average potential for demand reduction of wet appliances in Belgian households

to the power reserves for the TSO, 96 MW is not negligible. Primary reserves in Belgium are 100 MW, secondary are 137 MW. Tertiary power reserves in Belgium are 660 MW of which 240 MW can be regulated downward and 420 MW upward. The requirements for tertiary reserves are 90% availability for upward and 80% for downward control [38]. Wet appliances cannot be used for primary reserves because of the required response time which is less than 30 seconds. The required availability for secondary and tertiary reserves makes it hard to use appliances. However, wet appliances might be applied as a last resort for balancing.

Recent research [39] points out that, from a financial perspective, domestic smart energy appliances have significant value, but probably insufficient without additional incentives. The low potential per household in this paper confirms this finding.

VII. CONCLUSIONS

The research in this paper presents a data upscaling technique for time series and applies it to estimate the potential of demand reduction with wet appliances in Belgium. The estimation requires different techniques such as distribution based clustering and social segmentation.

A distribution based clustering technique is applied to a representative set to create a statistical model representative for the population. The model is adapted to work with relaxed cluster membership, allowing for data upscaling, which is only required when insufficient data are available.

The described technique is applied to estimate the potential for active demand reduction with wet appliances from a limited set of project data. The models representative for the population are created by applying Expectation Maximization clustering to time series measurements of a representative set of households. The project data is scaled up by working with relaxed cluster membership, allowing to scale up the data.

The potential for active demand reduction with wet appliances (washing machines, tumble dryers and dishwashers) is not only dependent on the electricity demand of the said appliances, but also of the attitude people have towards active demand with appliances. Four attitudes towards direct control of appliances are identified based on a survey. Only the most positive attitude is considered to be willing to participate.

By combining the attitudes towards demand response and the scaled up appliance data, the potential for demand reduction in Belgium is estimated to be 20.8 W per household on average, being higher during the weekend compared to during the week and higher in winter than in summer. The annual electricity demand of a typical (median) household is 3.6 MWh, which corresponds to an average power of 410 W.

When viewed over a large area, the potential for active demand reduction with wet appliances is about 4% of the total residential power and has about the same size as the primary reserves. The active demand by wet appliances does not meet the requirements for power reserves because of the response time and the availability requirements for reserves. Active demand with wet appliances can however be used as a last resort for balancing.

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REFERENCES

[1] U.S. Department of Energy, “Benefits of demand response in electricity markets and recommendations for achieving them, a report to the United States Congress pursuent to Section 1252 of the Energy Policy Act of 2005,” February 2006.

[2] L. Hancher, X. He, I. Azevedo, N. Keyaerts, L. Meeus, and J.-M. Glachant, “THINK topic 11: ‘Shift, not drift: Towards active demand response and beyond’,” European University Institute, Tech. Rep., 2013.

[3] D. Kirschen, “Demand-side view of electricity markets,” *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 520 – 527, 2003.

[4] H. Saele and O. Grande, “Demand response from household customers: Experiences from a pilot study in Norway,” *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 102–109, 2011.

[5] G. Strbac, “Demand side management: Benefits and challenges,” *Energy Policy*, vol. 36, no. 12, pp. 4419 – 4426, 2008.

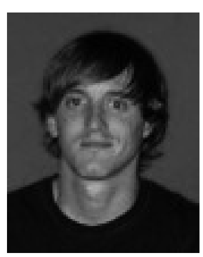
[6] K. Hamilton and N. Gulhar, “Taking demand response to the next level,” *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 60–65, 2010.

[7] J. Torriti, M. G. Hassan, and M. Leach, “Demand response experience in Europe: Policies, programmes and implementation,” *Energy*, vol. 35, no. 4, pp. 1575 – 1583, 2010.

[8] J. Kim and A. Shcherbakova, "Common failures of demand response," *Energy*, vol. 36, no. 2, pp. 873 – 880, 2011.
[9] T. Ericson, "Short-term electricity demand response," Ph.D. dissertation, Norwegian University of Science and Technology, Department of Electrical Power Engineering, 2007.
[10] D. Hammerstrom, T. Ambrosio, R. amd Carlon, J. DeSteese, G. Horst, R. Kajfasz, L. Kiesling, P. Michie, R. Pratt, M. Yao, J. Brous, D. Chassin, R. Guttromson, O. Jarvegren, S. Katipamula, N. Le, T. Oliver, and S. Thompson, "Pacific Northwest GridWise Testbed Demonstration Projects, Part I. Olympic Peninsula Project," Pacific Northwest National Laboratory, Tech. Rep., 2007.
[11] C. Bartusch, F. Wallin, M. Odlare, I. Vassileva, and L. Wester, "Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception," *Energy Policy*, vol. 39, no. 9, pp. 5008 – 5025, 2011.
[12] J. Torriti, "Price-based demand side management: Assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy," *Energy*, vol. 44, pp. 576 – 583, 2012.
[13] W. Labeeuw and G. Deconinck, "Customer sampling in a smart grid pilot," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012.
[14] M. Pipattanasomporn, M. Kuzlu, S. Rahman, and Y. Teklu, "Load profiles of selected major household appliances and their demand response opportunities," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 742 – 750, 2014.
[15] R. Stamminger, *Synergy Potential of Smart Domestic Appliances in Renewable Energy Systems*. Shaker, 2009.
[16] T. Lui, W. Stirling, and H. Marcy, "Get smart," *IEEE Power Energy Mag.*, vol. 8, no. 3, pp. 66 – 78, 2010.
[17] A. Soares, Á. Gomes, and C. Antunes, "Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 490 – 503, 2014.
[18] B. Dupont, P. Vingerhoets, P. Tant, K. Vanthournout, W. Cardinaels, T. De Rybel, E. Peeters, and R. Belmans, "Linear breakthrough project: Large-scale implementation of smart grid technologies in distribution grids," in *Innovative Smart Grid Technologies (ISGT Europe), 2012 3rd IEEE PES International Conference and Exhibition on*, Berlin, 2012.
[19] W. Labeeuw and G. Deconinck, "Residential electrical load model based on mixture model clustering and markov models," *IEEE Trans. Ind. Informat.*, vol. 9, no. 3, pp. 1561 – 1569, 2013.
[20] G. Chicco, R. Napoli, and F. Piglione, "Comparisons among clustering techniques for electricity customer classification," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 933 – 940, 2006.
[21] G. Chicco, "Overview and performance assessment of the clustering methods for electrical load pattern grouping," *Energy*, vol. 42, pp. 68 – 80, 2012.
[22] G. Tsekouras, N. Hatziargyriou, and E. Dialynas, "Two-stage pattern recognition of load curves for classification of electricity customers," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1120 – 1128, 2007.
[23] T. Zhang, G. Zhang, J. Lu, X. Feng, and W. Yang, "A new index and classification approach for load pattern analysis of large electricity customers," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 153 – 160, 2012.
[24] G. Coke and M. Tsao, "Random effects mixture models for clustering electrical load series," *Journal of Time Series Analysis*, vol. 31, no. 6, pp. 451 – 464, 2010.
[25] M. Sforna, "Data mining in a power company customer database," *Electric Power Systems Research*, vol. 55, no. 3, pp. 201 – 209, 2000.
[26] S. Verdu, M. Garcia, C. Senabre, A. Marin, and F. Franco, "Classification, filtering, and identification of electrical customer load patterns through the use of self-organizing maps," *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1672–1682, 2006.
[27] S. Valero, M. Ortiz, C. Senabre, C. Alvarez, F. Franco, and A. Gabaldon, "Methods for customer and demand response policies selection in new electricity markets," *Generation, Transmission Distribution, IET*, vol. 1, no. 1, pp. 104 – 110, 2007.
[28] I. Witten and E. Frank, *Data Mining: Practical Machine Learning Tools and Techniques*, 2nd ed. Morgan Kaufmann, 2005.
[29] VREG, "Welk type verbruiker bent u ?" 2014. [Online]. Available: http://www.vreg.be/welke-verbruiker-bent-u
[30] F. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319 – 340, 1989.
[31] *IBM SPSS Modeler 15 Algorithms Guide*, IBM, 2012.
[32] J. Stragier, L. Hauttekeete, L. De Marez, and S. Claessens, "Towards more energy efficient domestic appliances? Measuring the perception of households on smart appliances," *Energy & Environment*, vol. 24, no. 5, pp. 689 – 700, 2013.
[33] B. Dupont, K. Dietrich, C. De Jonghe, A. Ramos, and R. Belmans, "Impact of residential demand response on power system operation: A belgian case study," *Applied Energy*, vol. 122, pp. 1 – 10, 2014.
[34] V. Venkatesh, M. Morris, G. Davis, and F. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425 – 478, 2003.
[35] Directorate General for Statistics and Economic Information Belgium, "Structuur van de bevolking," 2011. [Online]. Available: http://statbel.fgov.be/
[36] D. Woitrin and F. Possemiers, "Studie (F)111013-CDC-1113 over 'de geïnstalleerde capaciteit voor de productie van elektriciteit in België in 2010 en de evolutie ervan'," Commissie voor de Regulering van de Elektriciteit en het Gas (CREG), Tech. Rep., September 2011.
[37] Federal Public Service Economy, SMEs, Self-Employed and Energy, "De energiemarkt in 2009," 2011. [Online]. Available: http://statbel.fgov.be/nl/binaries/1585-11-01%20De%20energiemarkt%20in%202009_tcm325-140066.pdf
[38] D. Woitrin and F. Possemiers, "Beslissing (B)101223-CDC-1027 over 'de vraag tot goedkeuring van de evaluatiemethode voor en de bepaling van het primair, secundair en tertiair reservevermogen voor 2011'," Commissie voor de Regulering van de Elektriciteit en het Gas (CREG), Tech. Rep., December 2010.
[39] M. Vlot, J. Knigge, and J. Slootweg, "Economical regulation power through load shifting with smart energy appliances," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1705 – 1712, 2013.

BIOGRAPHIES

Wouter Labeeuw received the M.Eng. degree in electronics-ict from Provinciale Industriële Hogeschool, Kortrijk, Belgium, in 2007, the M.Sc. degree in computer science from the Katholieke Universiteit Leuven (KU Leuven), Leuven, Belgium, in 2009 and the Ph.D. degree in engineering, in 2013, also from KU Leuven. He is currently a Postdoctoral Researcher at KU Leuven-ESAT/ELECTA and EnergyVille. His research interests include data analysis and demand side management.



Jeroen Stragier holds a M.Sc. in Communication Sciences and Marketing Analysis, in 2006 and 2007 respectively. He works as a researcher at iMinds-MICT-Ghent University since 2009. The main topics of his research are user adoption of new communication technology with regard to health related behavior.

Geert Deconinck is full professor at KU Leuven, and head of the research ESAT/ELECTA with 5 professors and approx. 60 Ph.D. students. His research interest focuses on the design and evaluation of robust control systems for electrotechnical applications in general and smart grids in particular. For the research institute EnergyVille, he is the scientific responsible for the Algorithms, Modeling and Optimization team. He teaches topics related to industrial automation and electrical installations, smart grids and measurement techniques. He is a senior member of IEEE and a fellow of IET.